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Implicit aspect extraction in sentiment analysis: Review, taxonomy, oppportunities, and open challenges

Mohammad Tubishat[a], Norisma Idris[a,*], Mohammad A.M. Abushariah[b]

[a] *Department of Artificial Intelligence, Faculty of Computer Science and Information Technology, University of Malaya, 50603 Kuala Lumpur, Malaysia*
[b] *Computer Information Systems Department, King Abdullah II School of Information Technology, The University of Jordan, Amman, Jordan*

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ABSTRACT

Sentiment analysis is a text classification branch, which is defined as the process of extracting sentiment terms (i.e. feature/aspect, or opinion) and determining their opinion semantic orientation. At aspect level, aspect extraction is the core task for sentiment analysis which can either be implicit or explicit aspects. The growth of sentiment analysis has resulted in the emergence of various techniques for both explicit and implicit aspect extraction. However, majority of the research attempts targeted explicit aspect extraction, which indicates that there is a lack of research on implicit aspect extraction. This research provides a review of implicit aspect/features extraction techniques from different perspectives. The first perspective is making a comparison analysis for the techniques available for implicit term extraction with a brief summary of each technique. The second perspective is classifying and comparing the performance, datasets, language used, and shortcomings of the available techniques. In this study, over 50 articles have been reviewed, however, only 45 articles on implicit aspect extraction that span from 2005 to 2016 were analyzed and discussed. Majority of the researchers on implicit aspects extraction rely heavily on unsupervised methods in their research, which makes about 64% of the 45 articles, followed by supervised methods of about 27%, and lastly semi-supervised of 9%. In addition, 25 articles conducted the research work solely on product reviews, and 5 articles conducted their research work using product reviews jointly with other types of data, which makes product review datasets the most frequently used data type compared to other types. Furthermore, research on implicit aspect features extraction has focused on English and Chinese languages compared to other languages. Finally, this review also provides recommendations for future research directions and open problems.

1. Introduction

In the last decade, the research community has witnessed various technological improvements and increase in the internet activities such as e-commerce, discussion forums, chatting, merchant's/manufacture's websites, social media communications, and many other online activities, which were able to provide positive impact on many research initiatives (Ravi & Ravi, 2015).

Sentiment Analysis (SA) or Opinion Mining (OM) is among the fields that benefited from these technological advancements and the internet, which is generally defined as the computerized process of recognizing, detecting, and determining the orientation of human opinion or emotion, which is directed towards different entities. Individuals normally post their opinions or emotions for

* Corresponding author.
E-mail addresses: mtubishat@siswa.um.edu.my (M. Tubishat), norisma@um.edu.my (N. Idris), m.abushariah@ju.edu.jo (M.A.M. Abushariah).

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products, services, hotels, movies, restaurants, political issues, or any other entity of their interest. Opinions, sentiments, and emotions can be captured using the individual's writings, facial expressions, speech, and many other media (Yadollahi, Shahraki, & Zaiane, 2017)

From applications perspective, there are many applications of SA in our daily life, where SA can be used for monitoring and analyzing the public opinions regarding political issues. SA can also be used in market intelligence (Li & Li, 2013), measuring the degree of user satisfaction on products or services and improving their weaknesses (Kang & Park, 2014), forecasting of price changes according to news sentiments, developing new products and services, and promoting and improving products according to customers' reviews. Being more trustworthy products and services' reviews as posted by their users compared to the vendor's reviews, many individuals rely on these reviews to make their decisions about the products, services, and other entities (Ravi & Ravi, 2015).

According to the previous studies (Medhat, Hassan, & Korashy, 2014; Rana & Cheah, 2016; Yadollahi et al., 2017), SA can be classified into three main levels, which are document level, sentence level, and aspect level. In document and sentence level the main aim to find the sentiment of overall document or sentence, while in aspect level the task to find the sentiment of each aspect as a single unit. In order to develop and evaluate SA at aspect level, features extraction is a crucial process, which can either be implicit or explicit.

This paper presents a review that aims to provide a comprehensive overview on different studies done on implicit aspect extraction, which to the best of our knowledge, serves as the first comprehensive review for implicit aspect extraction in SA. This review classifies and summarizes all the proposed research works on implicit aspect extraction and provides researchers with the current state-of-the-art in this field in order to assist them for further findings, and possible directions for new algorithms and improvements to the available works. Various taxonomies, open challenges, and future directions on implicit aspect extraction in SA are also highlighted in this review.

The rest of the review is organized as follows: in Section 2, we present the taxonomy of SA and background information towards the review. In addition, we provide a summary of different implicit aspects extraction techniques according to the extraction method used, which are either unsupervised, semi-supervised, or supervised. In Section 3, we present the results and discuss the analysis of the results and highlight some future researches and open problems in Section 4. We finally present the conclusions in Section 5.

2. Taxonomy of sentiment analysis

From the previous studies (Medhat et al., 2014; Rana & Cheah, 2016; Yadollahi et al., 2017), sentiment analysis can be classified into document, sentence, and aspect levels as illustrated in Fig. 1.

From document level perspective, the task is to extract all opinion words inside the whole document, which can either be long or short, in order to determine the polarity of the overall document without finding the polarity of each feature as a single case. The result in this case will be the overall opinion of the document. In the document level, SA considers the whole document as one topic and decides whether the overall opinion of the document is a positive opinion or a negative opinion based on some opinion words. This type of SA is very crucial for applications within social and psychological studies in social networks, consumer satisfaction, analyzing patients in medical settings, and many others (Yadollahi et al., 2017).

In addition, from sentence level perspective, the process is to find the polarity at the overall sentence without considering each feature as a single case and provide the opinion at the overall sentence level. As early as possible, it is important to identify whether the target sentence is subjective or objective and decide whether the overall opinion of the sentence is a positive opinion or a negative opinion for subjective sentences that are considered small documents. This type of SA is normally influenced by the surrounding context of the sentence, and is considered very crucial for applications that deal with tweets, Facebook posts and comments, short messages, and many others.

Finally, the aspect level that is also known as feature level is a fine-grained model of SA that deals with determining the opinion intended by people to a specific feature (aspect) of a product, service, or any entity (Medhat et al., 2014; Rana & Cheah, 2016; Yadollahi et al., 2017). In order to conduct a SA task based on aspect level, it is essential to extract the entities and their corresponding aspects/features or also referred to as opinion targets and their opinion words from given opinionated reviews. Thereafter,

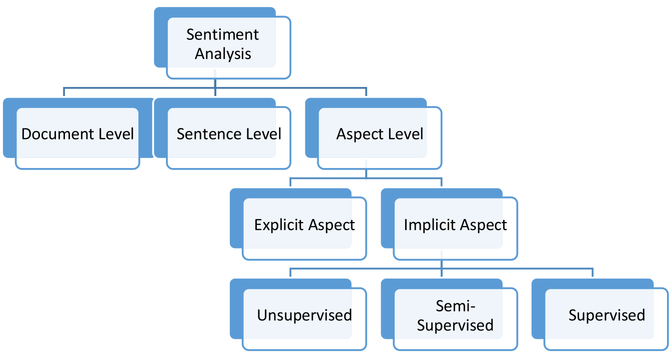

Fig. 1. Taxonomy of sentiment analysis.

Comment 1. *Although this mobile phone is too heavy, it has nice exterior and is little cheap.*
Comment 2. *The sound quality of this phone is very good*

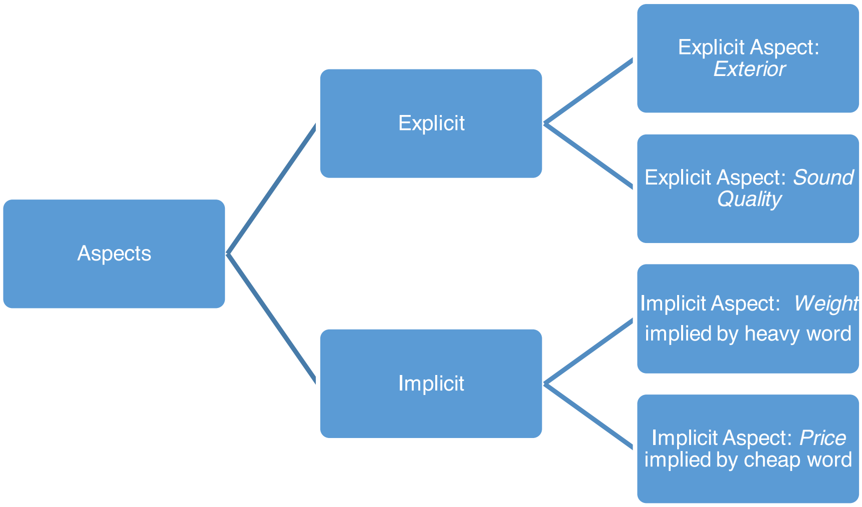

Fig. 2. Explicit and implicit features for mobile phone reviews.

the polarity of opinions directed to a given aspect is determined. The results of the SA task at aspect level are finally summarized and visualized (Rana & Cheah, 2016). Based on Fig. 1, the extracted feature can either be explicit or implicit, where the feature is considered explicit if it is mentioned explicitly in the review sentence otherwise it is considered implicit (Hu & Liu, 2004). Fig. 2 shows an example of both explicit and implicit features for mobile phone reviews based on the given comments.

The customers' reviews contain explicit aspects with also an important portion of the opinion aspect that is not mentioned explicitly but implied implicitly. According to Xu, Zhang, and Wang (2015), 30% of the Chinese reviews contain an implicit aspect. The huge amount of research for feature extraction was done for explicit features with few research attempts that have been done for implicit features extraction. A review on implicit aspect extraction is required as high percentage of customers based on that reviews for their buying decision.

In this review, 45 articles on implicit aspect extraction that span from 2005 to 2016 have been reviewed and analyzed. These articles were selected by first searching the online databases for articles which related to aspect extraction at aspect level. The downloaded articles were then divided into three categories: (1) explicit aspect extraction; (2) explicit and implicit aspects extraction; and (3) implicit aspect extraction. Since our focus is on the implicit aspect extraction, we selected and reviewed those articles from categories 2 to 3 only. We still considered those articles from category 2 which used both explicit and implicit aspects extraction as we need to study the implicit aspect extraction methods used in these articles. Finally, only articles related to implicit aspect extraction are included in our survey, which consists of 45 articles.

The collected articles are classified according to the proposed extraction method. By noticing the huge number of articles published every year in the area of SA, as it can be considered as a fertile area of research. For example, the survey conducted by Schouten and Frasincar (2016) focused only on aspect-level of SA. On the other hand, the survey conducted in Medhat et al. (2014) focused on SA at sentence and document levels, specifically on the feature selection methods used such as Chi-square, and Pointwise Mutual Information (PMI), and Sentiment Classification (SC) techniques that can be divided into 3 approaches: (1) machine learning; (2) lexicon-based; and (3) hybrid. In other survey conducted in Ravi and Ravi (2015), they focused on giving an overview about SA approaches, techniques, and applications at levels other than the aspect level. In addition, the survey conducted in Rana and Cheah (2016) mainly focus on reviewing different techniques used in explicit aspect extraction. Moreover, they categorized these explicit aspect extraction techniques according to the adopted method used in explicit aspect extraction and the algorithm used in each work. Furthermore, they presented a comparison amongst the performance of the included explicit aspect extraction techniques. Finally, the authors focus on explicit aspect extraction techniques at aspect-level SA. In the survey conducted by Yadollahi et al. (2017), they focus on emotion mining related works. They reviewed the methodologies used in emotion mining by making summary of the current methods used in emotion mining. In addition, they gave a summary and comparison of emotion mining methods applied for Twitter and classification works with Multi Labels Emotion. Furthermore, they provided a summary of emotion mining works which conducted using other languages than English.

This huge number of researches motivated us to conduct this review to help other researchers in this area. However, these previous studies presented little emphasis on implicit feature extraction. Recently, implicit feature extraction has attracted the interest of many researchers in SA field because of its importance in the overall review. In this review, we focus on implicit aspect extraction techniques. This work is organized by classifying the collected articles into three main categories according to the extraction method used, namely, unsupervised, semi-supervised, and supervised with a short summary of each technique, which are

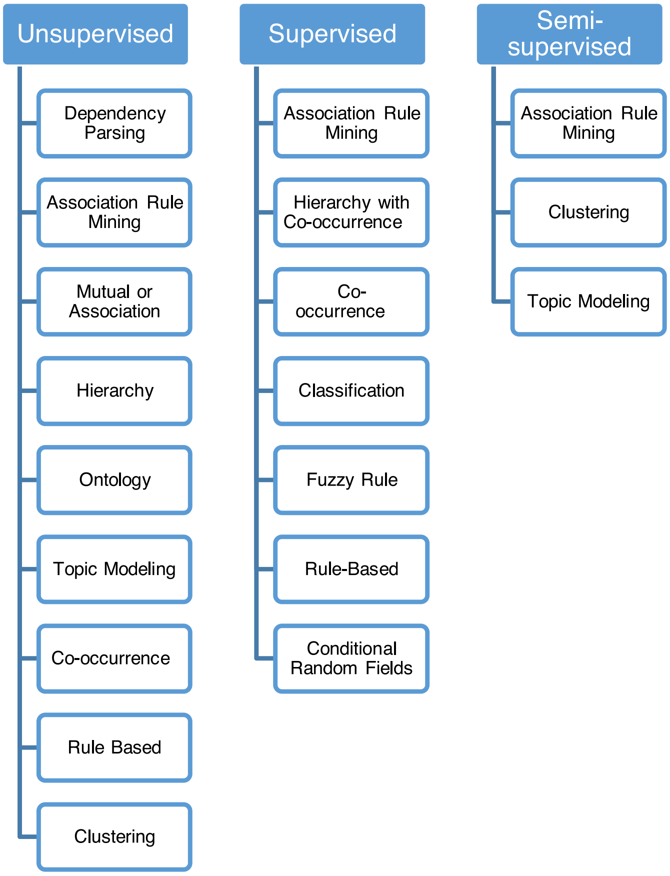

Fig. 3. Taxonomy of implicit feature extraction techniques.

presented in detail in a taxonomy in the following sections. Fig. 3 summarizes the taxonomy of implicit feature extraction techniques used in the previous research works.

2.1. Unsupervised implicit aspects extraction

Unsupervised implicit aspects extraction uses unlabeled data to extract implicit aspects from the corpus and not use any algorithm that require some training. Based on our reviews of the literatures, the most commonly used unsupervised implicit aspects extraction methods are dependency parsing, association rule mining, mutual or association, hierarchy, ontology, topic modeling, co-occurrence, rule-based, and clustering. The description of each method is described as follows:

2.1.1. Dependency parsing

Dependency parsing is a commonly used method in SA, which is based on the use of previously defined set of rules between different words' types for extracting the opinion targets and their related sentiment words. The dependency relation rules depend on the grammatical relations between words and can be extracted using dependency parser. Based on our literature review, this method was used by Zainuddin, Selamat, and Ibrahim (2016) in order to conduct the implicit feature extraction using Hate crime reviews.

2.1.2. Association rule mining

Association rule mining based on finding frequent text patterns that can co-occur together to find a sort of association between frequent items. It formulate the problem as an association rule in the form of $X => Y$, where Y is the consequent and X is an antecedent. This technique is based on two measures, namely, support and confidence. Market basket analysis is the famous example that association rule mining was applied to. Market basket analysis is based on determining customer frequent buying patterns based on identifying the associations existed in common among the selected items (Karthikeyan & Ravikumar, 2014).

Hai, Chang, and Kim (2011) used the concept of association rule mining by firstly creating co-occurrence frequency matrix between the opinion words and explicit features in the used corpus. Consequently, they extracted a set of association rules between the explicit features and opinion words by searching the constructed co-occurrence matrix. The opinion word in the rule represents the rule antecedent and explicit feature represents the rule consequent. The authors have then clustered the similar explicit features (rule consequent) in the extracted rules to have more robust association rules. If an opinion word exists in the sentence with no explicit feature, the opinion word was checked against the rules antecedent. From the matched rules, they took the rule consequents as the correct implicit feature from the rule with highest frequency.

According to Zhang, Xu, and Wan (2012), association rule mining is used for extracting the implicit features from Chinese cosmetic reviews. These rules were improved with the use of collocation statistics and Pointwise mutual information (PMI).

In a research work conducted by Mankar and Ingle (2015), the implicit features were extracted from the tourism reviews. First, they constructed the co-occurrence frequency matrix between the explicit features and opinion words. They considered two types of opinion words, which included adjectives and adverbs. Then based on that co-occurrence matrix, they created a set of association rules. These rules acted as a mapping function for the corresponding implicit feature.

2.1.3. Mutual or association

In this approach, they based on the association relation between words. In a previous work done by Su, Xiang, Wang, Sun, and Yu (2006), PMI technique based on semantic association analysis was used to extract the implicit features. They predefined the basic features of automobile as the possible candidate features for the implicit features. They then used PMI to find the implicit feature for the given opinion word from the predefined features set, but no quantitative performance results were provided. In another work done by Su et al. (2008), they used mutual reinforcement for clustering the features with opinion words. They created the clusters based on the hidden sentiment association that were found between the product features and opinion words. They then mapped the opinion words to the given implicit features by using these associations in the created clusters.

Wang and Wang (2008) extracted explicit features and their opinion words, and they used mutual information formula to find the association between features and opinion words in each extracted pair. The feature that has the highest association value with the opinion word in the implicit context was then considered as the correct implicit feature. Meng and Wang (2009) extracted the implicit features by using either the association between the opinion words and explicit features or the association between the features and unit of measurements.

Yu, Zha, and Chua (2012) extracted the implicit aspects based on the existed associations between the aspects' nodes in the constructed hierarchy and their corresponding reviews. They attached every node in the hierarchy with their related reviews. Subsequently, the opinion word that has no explicit aspect was used to lookup the reviews in the hierarchy. As a result, the aspect in hierarchy that has the same opinion word in the attached reviews was extracted as the correct implicit aspect. In addition, Yan, Xing, Zhang, and Ma (2015) extracted both explicit and implicit features using NodeRank algorithm to identify the association between the explicit features and opinion words in each extracted pair. They retrieved all feature-opinion pairs that have the same opinion word. As a result, the feature with the highest NodeRank value was selected from the candidate pairs as the correct implicit feature.

Song, Chu, Hu, and Liu (2013) extracted implicit aspects using Wikipedia and associations between words. They used Wikipedia to find the association between words using cosine similarity. They then retrieved the synonyms of the words to extract the implicit aspects.

2.1.4. Hierarchy

In Yu, Zha, Wang, Wang, and Chua (2011) work, product hierarchy for implicit aspect extraction was used. To create the used hierarchy, at first, they retrieved the initial product hierarchy from the product website. For each aspect node in the hierarchy, they attached it with all reviews in which the same aspects are mentioned and opinionated. For each aspect, they then translated the aspect attached reviews into a vector, which contains all the sentiment terms in the mentioned reviews. Furthermore, they calculated the centroid for each aspect as the average value of all sentiment terms in the aspect vector. The cosine similarity between the implicit context sentence and the centroid of each aspect is then calculated. Finally, the aspect with highest similarity value was selected as the correct implicit aspect.

2.1.5. Ontology

In Qiu (2015) work, semantic ontology for the implicit feature extraction was used. In ontology, for each entity all related aspects are linked with a sort of semantic relations. They extracted all opinion words that have no explicit features. Then they defined equations for measuring the semantic similarity between features and opinion words based on the ontology used. Lastly, they extracted the implicit feature based on the calculated associations. Another research work was conducted by Cadilhac, Benamara, and Aussenac-Gilles (2010) to extract implicit features based on ontology properties, which link the concepts in the ontology. For each opinion word without an explicit feature they considered the existence of an implicit feature.

Lazhar and Yamina (2016) used ontology for implicit feature extraction where they exploited the semantic relationships between concepts, attributes, and individuals in the ontology for implicit feature extraction. First, they extracted the opinion expressions that have no dependency relation to any explicit feature. They considered six types of dependency relations between opinion words and their related features. Then, they used opinion expression to navigate the ontology and find its corresponding implicit feature.

2.1.6. Topic modeling

Topic modeling technique depends on searching the document for all included topics where in SA, these topics represent the aspects (Rana, Cheah, & Letchmunan, 2016).

Santu, Sondhi, and Zhai (2016) used probabilistic model for implicit feature extraction. They modeled the reviews into models using generative probabilistic feature models. The reviews were represented as an association between sentences and features using hidden variables. They predefined and tagged the available explicit features in the used reviews as training data. Then they used the tagged training data to calculate the model parameters using expectation–maximization technique. Lastly, they extracted the implicit features using hidden variables and the calculated parameters values.

Sun, Chen, Li, and Peng (2015) used joint topic model for implicit features extraction. They classified the opinion words that are related to implicit features into two types, namely, special, and general opinion words. General opinion words can co-occur with many different features, whereas special opinion words co-occur only with one specific feature. They calculated two probability distributions, which included one for opinion distribution of the topics and the other one for the context distribution of both topics and opinions. Finally, they used these values for implicit feature extraction based on opinion word type.

Chen, Sun, Peng, and Huang (2015) created co-occurrence matrix, which also included the distance between each opinion word and other contexts. They also retrieved the topic probability distribution for a given opinion word using Latent Dirichlet Allocation (LDA) topic model. Consequently, they got context weight using cosine similarity through finding the similarity between the context distributions and the previously retrieved topic distributions. Lastly, they retrieved a set of implicit features' candidates that are related to the given opinion word based on the calculated context weight of these candidate features.

Xu, Cheng, Tan, Liu, and Shen (2013) used the developed aspect dependent sentiment lexicons for implicit feature identification. They used Joint Aspect Sentiment (JAS) model, which is based on generative topic model to extract the explicit aspects and find the entries of aspect-dependent sentiment lexicon. They also used the lexicon for implicit aspect identification based on the use of the information and knowledge of a specific opinion words as a clue that can be used to identify the implicit aspects.

2.1.7. *Co-occurrence*

In this technique, the main idea of implicit aspect extraction depends on the co-occurrence relation between the opinion word and the opinion target.

Zhang and Zhu (2013) used improved co-occurrence matrix for implicit feature extraction. They extracted explicit features and their related opinion words using double propagation (Qiu, Liu, Bu, & Chen, 2009). In addition, they also used the extracted feature and opinion words for building the co-occurrence matrix. This created matrix not only contains the co-occurrence frequencies between the explicit features and their opinion words, but also co-occurrence frequencies between the extracted explicit feature and other notional words in the sentence. Lastly, for each opinion word without an explicit feature, they searched the co-occurrence matrix for the features that co-occurred with the given opinion word. Based on the retrieved candidate implicit features, the feature that mostly co-occurred with other notional words in the sentence was selected.

In Bagheri, Saraee, and De Jong (2013) work, a graph is created based on the co-occurrence between the explicit features and their related opinion words. They also labeled each edge in the graph with the number of co-occurrences of their feature and opinion word. They not only used co-occurrence value, but also added to the co-occurrence value a weight, which represents the degree of association between the given edge feature and opinion word. In addition, for each opinion word without an explicit feature, they mapped it to the graph. Finally, the feature in the pair that has the same opinion word and highest edge value was extracted as an implicit feature.

Sun, Li, Li, and Lv (2014) extracted implicit features based on implicit features context and the co-occurrence between the explicit features and their opinion words. They created the co-occurrence matrix between the explicit features and their opinion words. Then they filtered the matrix by pruning the noisy data, searched the co-occurrence matrix for each opinion word without an explicit feature, and retrieved the list of implicit features candidate. Lastly, from the implicit features' candidates, they selected the feature that has the highest similarity with the implicit context.

In Prasojo, Kacimi, and Nutt (2015) work, they extracted implicit aspects by creating co-occurrence matrix between all extracted entities, opinion words, and explicit aspects. They also searched for both an entity and an opinion word that have no explicit aspects. Furthermore, they extracted the explicit aspect that co-occurred with this entity and opinion word. The explicit aspect that has the highest number of co-occurrence was selected as the implicit aspect. In case there are more than one aspects with the same highest number of co-occurrences, they used WordNet to find the similarity between the candidate's aspects and the sentence context. Lastly, the aspect with highest similarity was retrieved as the correct implicit aspect.

Rana and Cheah (2015) extracted implicit aspect based on Normalized Google Distance (NGD) and co-occurrence between the explicit aspects and opinion words. They searched all opinion words without explicit aspect, and extracted all explicit aspects that co-occur with the given opinion word as implicit aspect candidates. They also calculated the NGD between the candidate's aspects and the given opinion word. The candidate aspect with minimum NGD was selected as the correct implicit aspect. Makadia, Chaudhuri, and Vohra (2016) created co-occurrence frequency matrix between extracted explicit features and opinion words, and for each opinion word without an explicit feature they checked co-occurrence frequency matrix. The explicit feature that co-occurred with the given opinion word and has the maximum number of co-occurrence was extracted as implicit feature.

2.1.8. *Rule-based*

Wan, Nie, Lan, and Wang (2015) extracted implicit features by defining four rules based on Part-of-speech (POS) tags, and these rules are a combinations of POS tags. They assumed that implicit features are always considered as domain specific and divided into morphemes.

2.1.9. *Clustering*

Popescu and Etzioni (2007) extracted the opinion words related to explicit features, and grouped all extracted opinion words into a number of clusters. They also labeled these clusters with a label that represents the implicit feature for all opinion words in the given cluster. They mapped each opinion word without explicit feature to the previously identified cluster. The cluster label for the cluster that has the same opinion word was selected as implicit feature.

Table 1
Summary of unsupervised implicit aspect extraction.

References	Main Method used	Dataset details		Language details		Performance		
		Data domain	Data size	Language dependency	Language	R	P	F
Zainuddin et al. (2016)	Dependency parsing	Hate crime reviews	622 tweets	Independent	English	N/A	N/A	N/A
Hai et al. (2011)	Association rule mining	Product reviews	2986 reviews (351 reviews with 449 implicit sentences)	Independent	Chinese	0.7271	0.7629	0.7446
Zhang et al. (2012)		Product reviews	1087 reviews with 2757 sentences	Dependent	Chinese	0.9702	0.8915	0.9292
Mankar and Ingle (2015)		Tourism reviews	300 reviews	Independent	English	N/A	N/A	N/A
Su et al. (2006)	Mutual or association	Product reviews	N/A	Independent	Chinese	N/A	N/A	N/A
Su et al. (2008)			300 reviews	Independent	Chinese	N/A	N/A	N/A
Wang and Wang (2008)			900 reviews	Independent	Chinese	0.6562	0.5216	0.587
Meng and Wang (2009)			N/A	Independent	Chinese	0.79	0.71	0.748
Yu et al. (2012)			70,359 reviews with 197,714 sentences	Independent	English	0.643	0.726	0.682
Yan et al. (2015)			29,192 reviews	Dependent	Chinese	0.7	0.805	0.739
Song et al. (2013)			5000 sentences (4000 training, 1000 testing)	Dependent	Chinese	0.74	0.91	0.82
Yu et al. (2011)	Hierarchy	Product reviews	70,359 reviews with 197,714 sentences (29,657 implicit aspect sentences)	Independent	English	N/A	N/A	0.77
Qiu (2015)	Ontology	Product reviews	N/A	Independent	English	N/A	N/A	N/A
Cadilhac et al. (2010)		Restaurant reviews	58 reviews	Independent	French	0.7733	0.7692	0.7712
Lazhar and Yamina (2016)		Hotel reviews	150 reviews (100 training, 50 testing)	Independent	English	N/A	N/A	N/A
Xu et al. (2013)	Topic modeling	Restaurant and hotel reviews	N/A	Independent	English	N/A	N/A	N/A
Sun et al. (2015)		Product reviews	5731 reviews	Independent	Chinese	0.665	0.76	N/A
Chen et al. (2015)		Product reviews	314 reviews with 4259 sentences	Independent	English	0.624	0.673	N/A
Santu, Sondhi, and Zhai (2016)		Product reviews	314 reviews with 4259 sentences. 4699 reviews with 38,056 sentences.	Independent	English	0.497	0.59	0.5332
Sun et al. (2014)	Co-occurrence	Product reviews	6102 reviews	Independent	Chinese	0.7	0.68	NA
Zhang and Zhu (2013)		Product and clothes reviews	2000 sentences (714 implicit, 1286 explicit)	Independent	Chinese	Product 0.7951 clothes 0.7738	Product 0.8134 clothes 0.8017	NA
Bagheri et al. (2013)		Product reviews	314 reviews with 4259 sentences	Independent	English	NA	NA	NA
Prasojo et al. (2015)		News articles reviews	1087 reviews	Independent	English	0.7382	0.7312	0.7347
Rana and Cheah (2015)		Customer reviews	314 reviews with 4259 sentences	Independent	English	NA	NA	NA
Makadia et al. (2016)		Product reviews	N/A	Independent	English	0.7021	0.824	0.7582
Wan et al. (2015)	Rule-based	Clothes reviews	7300 reviews	Independent	Chinese	NA	NA	NA
Popescu and Etzioni (2007)	Clustering	Product and hotel reviews	314 reviews with 4259 sentences	Independent	English	NA	NA	NA
Liu et al. (2013)		Product reviews	3500 reviews with 9998 sentences	Dependent	Chinese	0.645	0.725	NA
Chen et al. (2016)		Product reviews	1500 reviews (1541 explicit features, 1108 implicit features)	Independent	English	NA	NA	NA

Liu, Lv, and Wang (2013) identified two types of opinion words, namely, vague opinion and clear opinion. The vague opinion cannot be defined without context information, whereas clear opinion has one possible implicit feature. They clustered opinion words with explicit features that are related to these opinion words in one cluster. Then, they searched for opinion words without an explicit feature. According to opinion word type, if it is a vague opinion it was replaced with an entity. Otherwise, they mapped it to the created clusters and they selected feature with the highest importance from the cluster that has the same opinion word.

Chen, Martineau, Cheng, and Sheth (2016) extracted the implicit features using a clustering technique. They assumed that the candidate implicit aspects are the adjectives and verbs. They clustered similar features in one cluster with one representative feature. Finally, the resulted feature cluster will be used to identify implicit features. Table 1 provides a summary of unsupervised research works on implicit aspects extraction.

2.2. Semi-supervised implicit aspects extraction

Semi-supervised implicit aspects extraction utilizes both labeled and unlabeled data to extract implicit aspects from the corpus or require little training. Based on our literature investigation, the most commonly used semi-supervised implicit aspects extraction methods can be based on association rule mining, clustering, and topic modeling. The following sections describe each method with sufficient details including research attempts for each method.

2.2.1. Association rule mining

Wang, Xu, and Wan (2013) used hybrid association rule mining for extracting the implicit features. Five collocation extraction techniques are used to calculate the number of co-occurrences between the explicit features and words that implied features. In addition, they created five sets of association rules from the created co-occurrences and they selected the top rules from these rules as basic rules set. They also extended these basic rules with more rules using another three methods namely, substring hypothesis, dependency grammar, and semi-supervised topic model. Finally, they used full set of rules, which included the basic rules and the extended rules to extract implicit features.

Jiang, Pan, and Ye (2014) used association rule mining technique for implicit aspects extraction. They used different types of implicit aspect indicators, semi-supervised LDA topic model, and enhanced algorithm for collocation extraction. The collocation algorithm used to extract the basic rules, and they extended these basic rules with new rules by using topic model. They removed redundant extracted aspect indicators by using pruning method. Lastly, the basic rules combined with the new rules were used to extract the implicit aspects.

2.2.2. Clustering

Hai, Chang, Cong, and Yang (2015) extracted explicit features and used K-means algorithm to group extracted explicit features into different clusters by grouping similar explicit features into one cluster. In each cluster, they considered the feature with highest frequency as the representative feature for the given cluster, and they also attached each cluster with their related opinion words. In addition, they calculated semantic correlation for each opinion word in the given cluster. Furthermore, for each opinion word without an explicit feature they mapped it to the opinion words' members of the created clusters. Finally, the representative feature of the matched cluster that has the highest correlation value with the given opinion word was selected as the implicit feature.

2.2.3. Topic modeling

Xu et al. (2015) extracted implicit features using semi-supervised methods using both Support Vector Machine (SVM) and explicit topic model. The LDA explicit topic model was improved with the use of cannot-link, must-link, and prior knowledge. Must-link relation gives information about the pair of words that must exist within the same cluster, whereas cannot-link relation gives information about the pair of words that cannot exist within the same cluster. Therefore, they used LDA explicit topic model with these improved features for selecting the relevant attributes from the dataset. Further, they initiated many SVM classifiers, which were trained on the selected attributes to extract the implicit features. Table 2 provides a summary of semi-supervised research works on implicit aspects extraction.

2.3. Supervised implicit aspects extraction

Supervised implicit aspects extraction uses labeled data to extract implicit aspects from the corpus or use any algorithm that requires training. Based on our literature investigation, the most commonly used supervised implicit aspects extraction methods can be association rule mining, hierarchy with Co-occurrence, co-occurrence, classification, fuzzy, rule-based, and conditional random fields. The following sections describe each method with sufficient details including research attempts for each method.

2.3.1. Association rule mining

Liu, Hu, and Cheng (2005) labeled each opinion word without an explicit feature in the dataset with its implicit feature. They also created a set of association rules from the labeled data. Furthermore, they pruned unused rules, and selected the rules that have features on their right side. Finally, they translated these rules into language patterns and used them in implicit feature extraction.

2.3.2. Hierarchy with co-occurrence

Panchendrarajan et al. (2016) manually labeled all opinion words without an explicit aspect with their implicit aspects. In

Table 2
Summary of semi-supervised previous research works.

References	Main method used	Dataset details		Language details		Performance		
		Data domain	Data size	Language dependency	Language	R	P	F
Wang et al. (2013)	Association rule mining	Product reviews	14218 sentences (3220 explicit features and 1410 implicit features)	Independent	Chinese	0.6725	0.861	0.7551
Jiang et al. (2014)			5704 sentences 4753 explicit sentence (features) 951 implicit sentence (features)	Independent	English	0.7365	0.8257	0.7786
Hai et al. (2015)	Clustering	Product and hotel reviews	7800 reviews products with 12,546 sentences. Hotels 4900 reviews with 18,239 sentences	Independent	Chinese	Cell phone 0.6993 Hotel 0.622	Cell phone 0.7299 Hotel 0.5809	Cell phone 0.7143 Hotel 0.6008
Xu et al. (2015)	Topic modeling	Product reviews	3140 explicit sentences (with 3140 explicit features) for training. 7043 non-explicit sentences for testing (with 1389 implicit features)	Dependent	Chinese	0.7005	0.8742	0.7778

addition, all sentences with labeled implicit aspects were extracted and grouped according to opinion words. After labeling and grouping sentences, they searched for each opinion word without an explicit aspect and extracted a list of its implicit aspect candidates. In the following step, they calculated a score for each implicit aspect candidate based on co-occurrence between opinion word and other words in the sentence from the matched opinion word grouped sentences. In addition, they selected implicit aspect candidates with score greater than the specified threshold and used double propagation (Qiu et al., 2009) to extract the explicit features in their implicit contexts. In addition, if the candidate implicit aspect has a relationship with the extracted explicit feature according to the hierarchy of restaurant domain, they considered it as a correct implicit aspect.

2.3.3. *Co-occurrence*

Schouten and Frasincar (2014b) labeled the dataset with the implicit aspects and computed the co-occurrence score between the labeled implicit aspect and other notional words in the sentence. In the last phase, the implicit aspect with the highest co-occurrence score with the notional words in the implicit sentence context was selected as a correct implicit aspect. Schouten et al. (2015) labeled all implicit aspects in the training dataset and then extracted synsets from WordNet for all words in the labeled implicit aspect sentence's context. After labeling implicit aspects and extracting synsets, they extracted all possible semantic relations associated each synset. In the following step, they created a co-occurrence matrix between the annotated implicit aspect and all synsets of other words in the sentence. They also improved this co-occurrence matrix by the semantic relations associated with each synset. In the last phase, they computed co-occurrence score based on this co-occurrence matrix values and the aspect with the highest score was selected as the correct implicit aspect.

Schouten and Frasincar (2014a) labeled the dataset with implicit aspects and in the next step they calculated the co-occurrence score between this labeled implicit aspects and other words in the sentence. From a set of implicit aspect candidates, they selected the aspect with maximum score and greater than the threshold value as the potential implicit aspect. They used the threshold filter to differentiate between the sentence that contains implicit aspect or not. To detect and extract more than one implicit feature per sentence, Dosoula et al. (2016) extended the work of Schouten and Frasincar (2014a). They predicted the existence of many implicit features in each sentence by using a classifier and score function which are based on the sentence characteristics.

2.3.4. *Classification*

Mohammed (2016) used a corpus, WordNet, and Naïve Bayes classifier as a hybrid approach for implicit aspect extraction. In the first step, they extracted all adjectives from the given corpus, then used WordNet to extract words with lexical relationships to the given adjectives such as their synonyms and antonyms. Finally, they used the extracted data to train Naïve Bayes classifier for implicit aspect extraction.

Zeng and Li (2013) extracted all explicit aspects and their opinion words, and for each opinion word they grouped all aspects that co-occur with the given opinion word into one cluster. In the following step, for each aspect-opinion pair in the given cluster they created a training document, which included all sentences that contain the same pair in the dataset. They also used a classifier to map the opinion word without an explicit aspect to one of the aspect-opinion pair training documents.

Fei, Liu, Hsu, Castellanos, and Ghosh (2012) used dictionary-based approach for identifying implicit aspect indicated by adjective opinion words. They further extracted all glosses for each opinion word from five online English dictionaries. In the second step, they extracted nouns from these glosses as potential implicit aspect candidates. Finally, based on these glosses and lexical relations, they used collective classification to classify and detect the adjective related nouns.

2.3.5. Fuzzy

Afzaal, Usman, Fong, Fong, and Zhuang (2016) extracted explicit and implicit aspects and their related opinion words. They used FURIA algorithm to build a set of fuzzy rules based on frequent explicit aspects. The rule has the opinion word as precondition and the explicit aspect as the corresponding result. They mapped each opinion word without an explicit aspect to the set of fuzzy rules. The matched rule that has the same opinion word and highest frequency, they extracted its corresponding aspect as an implicit aspect.

2.3.6. Rule-based

Poria, Cambria, Ku, Gui, and Gelbukh (2014) used implicit aspect lexicon and a rule-based approach for extracting implicit aspects. In this proposed technique, they created the lexicon based on the use of Implicit Aspect Indicators (IAC) from implicit aspect corpus, which was developed by Cruz, Gelbukh, and Sidorov (2014). Now, the lexicon contains each IAC and its corresponding implicit aspect. They also enriched the lexicon by IAC possible synonyms and antonyms from WordNet. In the last step, for each IAC word without an explicit aspect in the given sentence, they mapped it to its corresponding aspect category based on the predefined lexicon.

2.3.7. Conditional random fields

Bhatnagar, Goyal, and Hussain (2016) used Conditional Random Fields (CRF) for extracting the implicit feature in tourism review from TripAdvisor. In first step, they used CRF for building implicit feature recognizer for extracting the implicit aspect. In addition, the trained file resulted from using CRF was used for detecting implicit features indicators. However, the proposed idea is domain specific just for tourism reviews and cannot be used for other type of reviews such as product reviews. Table 3 provides a summary of supervised research works on implicit aspects extraction.

3. Analysis and discussion

In this section, we analyze and discuss the 45 articles on implicit aspect extraction that span from 2005 to 2016 as stated in Section 2. The analysis and discussion are according to several factors such as the implicit aspect extraction method used, advantages and disadvantages of different previous research works, datasets and languages used, and the obtained performance of previous research works.

3.1. Distribution of research works according to implicit aspect extraction methods

With reference to the taxonomy of implicit aspect extraction as stated in previous sections, Fig. 4 illustrates the researchers' preference in applying either unsupervised, semi-supervised, or supervised methods.

Based on Fig. 4, there are 29 articles out of the 45 articles who relied on unsupervised implicit aspect extraction methods, which makes about 64% of the total articles considered for this purpose. In addition, there are 4 articles out of the 45 articles who relied on semi-supervised implicit aspect extraction methods, which makes about 9% of the total articles considered for this purpose. Finally, supervised implicit aspect extraction methods were used in 12 articles out of the 45 articles, which makes about 27% of the total articles considered for this purpose. This shows that unsupervised methods can be considered as the most frequently used method for implicit feature extraction in the previous research works. This is due to the fact that unsupervised methods do not require data annotation for implicit features or any sort of training, which is also not time consuming for preparing the required annotated data. Although the difference between unsupervised methods and other types of methods is huge, supervised methods are the second highest in terms of usage. However, the supervised methods require labeled data and cannot be generalized easily. Finally, the semi-supervised methods are still unexplored sufficiently in comparison to other types of methods, which in turn gives an opportunity for researchers to further explore them and develop new techniques using these methods as there are comparable results of previous research works that were based on these methods in comparison with other research works that applied supervised or unsupervised methods.

3.2. Advantages and disadvantages of the previous research works

It is very crucial to highlight the advantages and disadvantages of the previous research works on implicit aspect extraction, which would assist the research community in their selection of the methods. Based on our analysis of the previous research works conducted on implicit aspect extraction, we are able to produce a list of 17 advantages of implicit aspect extraction as stated in Table 4, whereas Table 5 maps every advantage to its sources.

Based on our analysis of the previous research works conducted on implicit aspect extraction, we are able to produce a list of 5 disadvantages of implicit aspect extraction as stated in Table 6, whereas Table 7 maps every disadvantage to its sources.

The research community can use these above-mentioned advantages and disadvantages to further explore the available methods used for implicit aspect extraction, which in turn help them in making new solutions or making hybrid solutions based on the advantages and disadvantages of the methods.

Table 3
Summary of supervised previous research works.

References	Main method used	Dataset details		Language details		Performance		
		Data domain	Data size	Language dependency	Language	R	P	F
Liu et al. (2005)	Association rule mining	Product reviews	Reviews on 15 products with 10 products used for training and 5 for testing	Independent	English	N/A	N/A	N/A
Panchendrarajan et al. (2016)	Hierarchy with co-occurrence	Restaurant reviews	900 reviews training set 100 reviews for testing	Independent	English	0.758	0.947	0.842
Schouten and Frasincar (2014b)	Co-occurrence	Product reviews	3797 sentences (2726 implicit features and 1071 explicit features)	Independent	English	N/A	N/A	0.285
Schouten and Frasincar (2014a)		Product and restaurant reviews	314 reviews with 4259 sentences restaurant with 3044 sentences	Independent	English	N/A	N/A	+8.7 on product review +3.6 on restaurant review
Schouten et al. (2015)		Product and restaurant reviews	314 reviews with 4259 sentences restaurant with 3041 sentences	Independent	English	N/A	N/A	restaurant 0.794 product 0.704
Dosoula et al. (2016)		Restaurant reviews	3044 sentences	Independent	English	N/A	N/A	0.645
Fei et al. (2012)	Classification	N/A	310 adjectives	Independent	English	0.773	0.763	0.768
Mohammed (2016)		Product and restaurant reviews	314 reviews with 4259 sentences 3044 sentences with 5 implicit aspects types	Independent	English	Product 0.9036 restaurant 0.943	Product 0.956 restaurant 0.976	N/A
Zeng and Li (2013)		Product reviews	12760 sentences with 6050 explicit features and 2247 implicit features	Independent	Chinese	0.707	0.8383	0.7671
Afzaal et al. (2016)	Fuzzy	Restaurant and hotel reviews	Restaurants 2000 reviews, hotels 4000 reviews	Independent	English	N/A	N/A	Accuracy Restaurant0.79 Hotel 0.81
Poria et al. (2014)	Rule-based	Product reviews	314 reviews with 4259 sentences 7892 sentences in SemEval 2014	Independent	English	N/A	N/A	N/A
Bhatnagar et al. (2016)	Conditional random fields	Tourism reviews	N/A	Independent	English	N/A	N/A	N/A

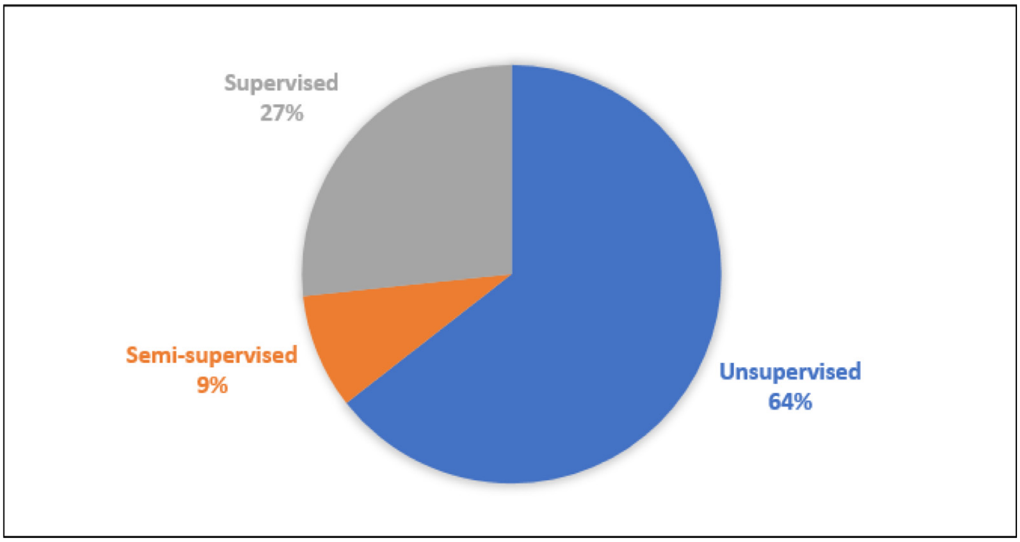

Fig. 4. Previous research works distribution according to extraction methods.

Table 4
Advantages of different previous research works on implicit aspect extraction.

Adv#	Advantage
1	No labeled data required
2	Considered the context in the implicit sentence in extraction process
3	Defined implicit aspects not only based on aspects that have been found as explicit aspects in the corpus, but also with other information sources
4	Included both opinion and notional words for implicit aspect extraction
5	Defined both the implicit aspects and its sub aspects
6	Included low frequency aspect words in implicit aspects extraction
7	Used many indicator types for implicit aspect extraction
8	Extracted multiple implicit aspects per sentence
9	Extracted implicit aspect at concept level
10	The use of very few parameters
11	Considered adversative words in implicit aspect extraction
12	Classified the opinion words into different types
13	Created new standardized datasets
14	Can be generalized easily
15	Solved the problem of aspects that rarely co-occur with the opinion words
16	Can predict the existence of multiple implicit aspects per sentence
17	Identify coreferential aspects

3.3. Datasets and languages

Fig. 5 presents the distribution of previous research works according to the used data domain. It is clearly noticed from Fig. 5 that 25 articles conducted the research work solely on product reviews, and 5 articles conducted their research work using product reviews jointly with other types of data. This makes product review datasets the most frequently used data type compared to other types. There are many other domain data areas that are not explored until now and require further works, which in turn open doors and challenges for researchers in future research, such as medical domains, airline reservations, and many others.

Fig. 6 presents the distribution of the previous research works on implicit aspect extraction according to the languages used. As noticed from Fig. 6, the most frequently used languages are English, followed by Chinese. To the best of our knowledge, other languages such as Spanish, Italian, Germanic, Arabic, Turkish, and many more are still unexplored, which open new horizons for researchers to explore these languages as future research by building new techniques and required resources for these languages such as implicit corpus. Furthermore, it is seen from the reviewed researches that some proposed techniques are language dependent and cannot be generalized easily.

3.4. Performance of the previous works

In the previous sections, we discussed a variety of implicit aspect extraction techniques. However, direct comparisons between these techniques are not applicable, as they use different datasets and/or different techniques. Therefore, in this section, we highlighted the performance based on the category type used namely, unsupervised, semi-supervised, or supervised. In addition, it is

Table 5
Advantages of different previous researches on implicit aspect extraction.

Adv#/Ref#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Liu et al. (2005)				√													
Hai et al. (2011)	√																
Zhang et al. (2012)						√											
Wang et al. (2013)				√													
Jiang et al. (2014)							√										
Mankar and Ingle (2015)	√																
Su et al. (2006)	√																
Su et al. (2008)	√																
Wang and Wang (2008)	√																
Meng and Wang (2009)	√																
Yu et al. (2012)	√				√												
Yu et al. (2011)	√				√												
Qiu (2015)	√				√												
Panchendrarajan et al. (2016)	√	√						√									
Cadilhac et al. (2010)	√								√								
Lazhar and Yamina (2016)	√																
Xu et al. (2013)	√																
Xu et al. (2015)				√						√							
Sun et al. (2015)		√									√	√					
Chen et al. (2015)		√															
Sun et al. (2014)	√	√															
Popescu and Etzioni (2007)	√																
Fei et al. (2012)	√		√												√		
Zhang and Zhu (2013)				√													
Bagheri et al. (2013)	√													√			
Schouten and Frasincar (2014b)				√													
Schouten and Frasincar (2014a)				√													
Yan et al. (2015)	√																
Prasojo et al. (2015)	√																
Mohammed (2016)	√		√														
Dosoula et al. (2016)								√								√	
Afzaal et al. (2016)	√																√
Makadia et al. (2016)	√																
Zeng and Li (2013)	√	√															
Wan et al. (2015)	√																
Zainuddin et al. (2016)	√																
Liu et al. (2013)	√																
Karmaker Santu et al. (2016)													√	√			
Chen et al. (2016)															√		
Song et al. (2013)	√		√														

Table 6
Disadvantages of different previous research works on implicit aspect extraction.

Dis#	Disadvantage
1	Required labeled data
2	Absence of context consideration in the implicit sentence
3	Only features that have been found as explicit features somewhere in the corpus can be chosen as implicit features
4	Unable to handle the case when the opinion words have many possible correct features
5	Considered adjectives as opinion words only

noticeable that there are some techniques that did not provide quantitative results and were not included in the performance figures. Furthermore, some articles did not use all common performance measures such as precision, recall, and f-measure, thus we only presented available results.

Fig. 7 illustrates the results of different unsupervised techniques that may use similar or different data domains, but for unsupervised research works provided the performance results as one value for both explicit and implicit aspects as illustrated in Fig. 8. From Fig. 7, it is clearly shown that the research work of Song et al. (2013) received a satisfactory results, as they did not base their work only on the used corpus, but also exploited the use of Wikipedia, to find the association between words. In addition, the research work of Zhang and Zhu (2013) also received good results as they exploited two relations' types namely, the relation between opinion words and explicit features, and the relation between the feature words and other notional words in the implicit sentence. As shown in Fig. 7, many other unsupervised works also obtained satisfactory results.

Fig. 8 presents a performance of different unsupervised research works that extracted both explicit and implicit aspects, but they provided the performance results of precision, recall, and *f*-measure which combined the performance of both implicit and explicit

Table 7
Disadvantages of different previous researches on implicit aspect extraction.

Dis#/Ref#	1	2	3	4	5	Dis#/Ref					
Liu et al. (2005)	√	√	√			Popescu and Etzioni (2007)		√			
Hai et al. (2011)		√	√			Fei et al. (2012)		√			√
Zhang et al. (2012)		√	√			Zhang and Zhu (2013)			√		
Wang et al. (2013)		√	√	√		Bagheri et al. (2013)		√	√		
Jiang et al. (2014)		√	√	√		Schouten and Frasincar (2014b)	√		√		
Mankar and Ingle (2015)		√				Schouten and Frasincar (2014a)	√		√		
Su et al. (2006)		√	√		√	Yan et al. (2015)		√	√		
Su et al. (2008)		√			√	Prasojo et al. (2015)					√
Wang and Wang (2008)		√	√			Rana and Cheah (2015)		√			
Meng and Wang (2009)		√				Schouten et al. (2015)	√				
Yu et al. (2012)		√				Mohammed (2016)		√			√
Hai et al. (2015)		√	√			Dosoula et al. (2016)	√	√			
Yu et al. (2011)		√				Afzaal et al. (2016)			√		
Qiu (2015)		√	√			Makadia et al. (2016)		√	√		
Panchendrarajan et al. (2016)	√		√			Zeng and Li (2013)			√		
Cadilhac et al. (2010)		√	√			Zainuddin et al. (2016)		√			
Lazhar and Yamina (2016)		√	√			Liu et al. (2013)		√			
Xu et al. (2013)		√	√			Poria et al. (2014)	√	√			
Xu et al. (2015)	√	√	√			Karmaker Santu et al. (2016)			√		
Sun et al. (2015)			√			Bhatnagar et al. (2016)					
Chen et al. (2015)					√	Chen et al. (2016)		√			
Sun et al. (2014)					√	Song et al. (2013)		√			

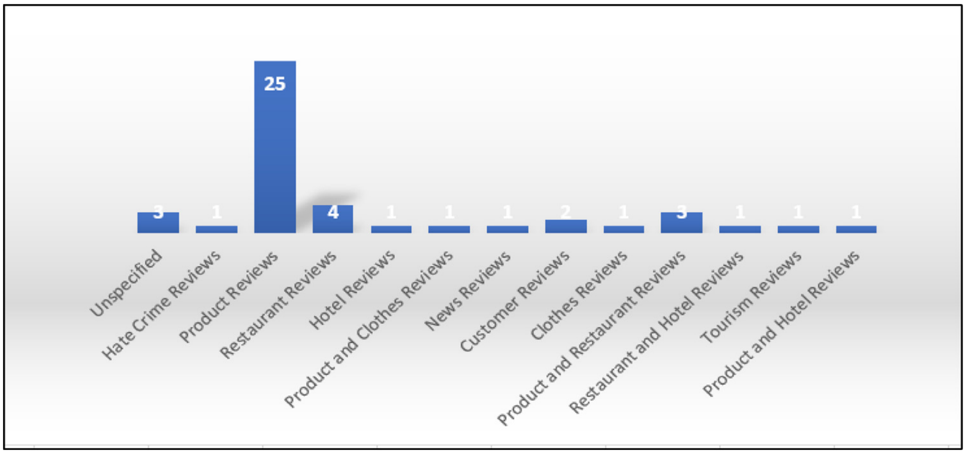

Fig. 5. Previous works distribution according to used data domain.

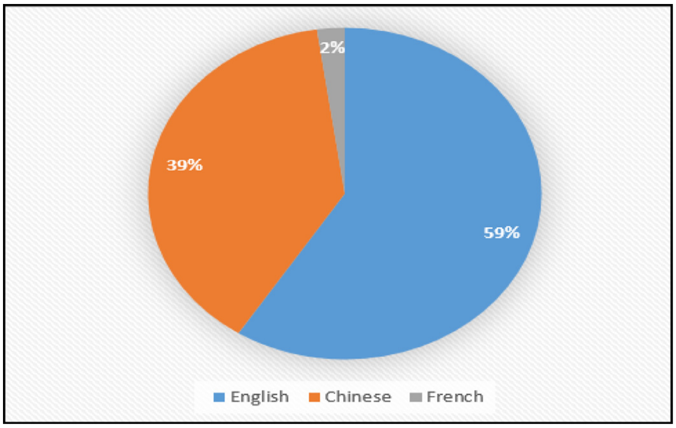

Fig. 6. Previous works distribution according to used language.

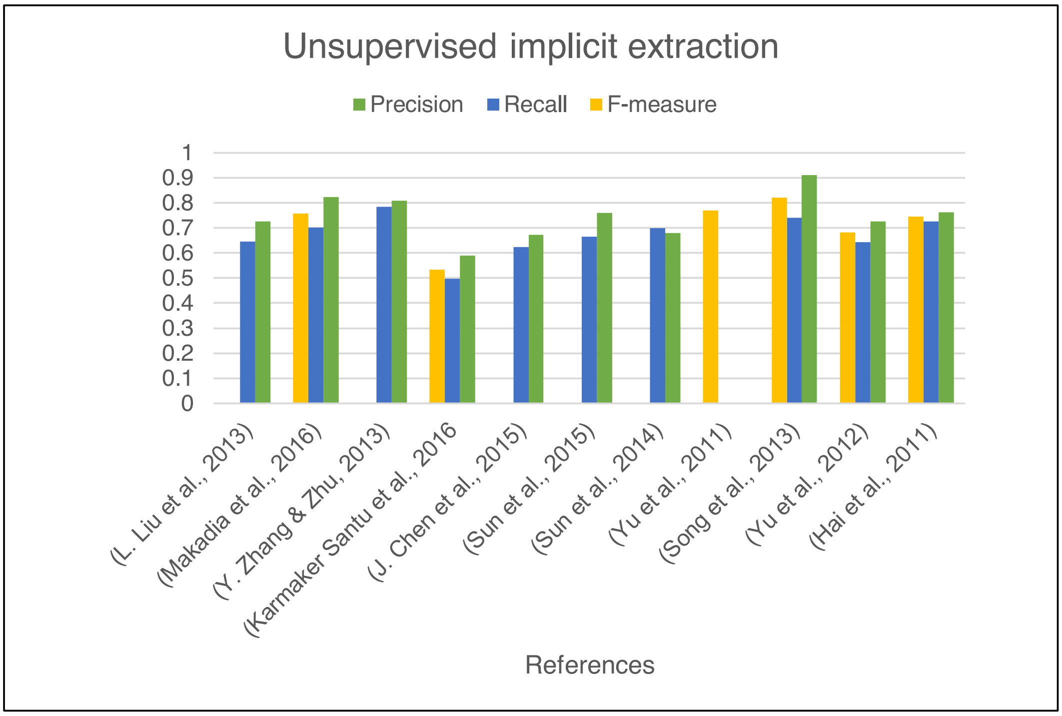

Fig. 7. Performance of unsupervised implicit aspect extraction research works.

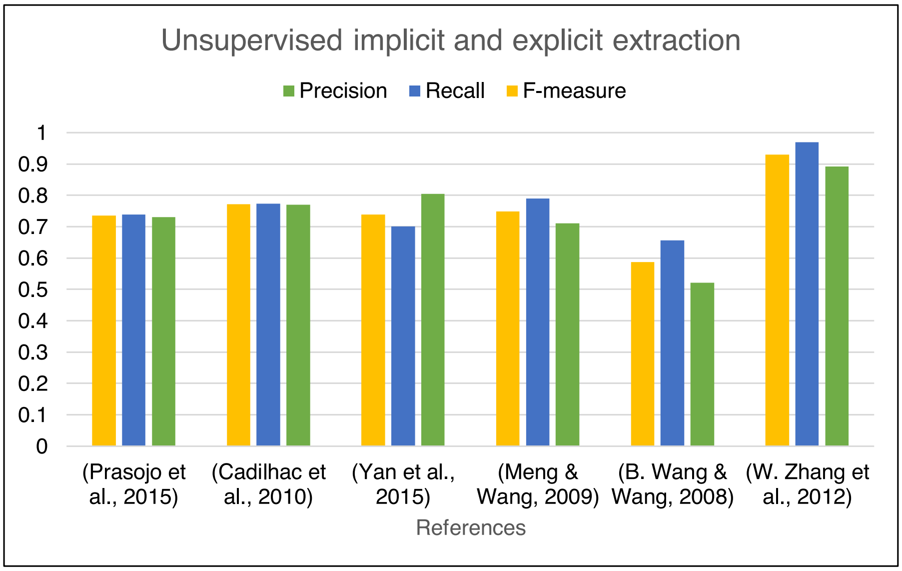

Fig. 8. Performance of unsupervised research works extracted both explicit and implicit aspects and provided the results for both in one value.

aspects extraction together. As shown in Fig. 8, the research work conducted by Zhang et al. (2012) obtained a satisfactory results, as they used more rules and paid attention to low frequency words. Furthermore, by looking at other works it is noticed that there are also good results. However, in the research conducted by Wang and Wang (2008) they obtained the low results, as they just based their work on the used corpus for finding implicit aspects without using other knowledge resources.

Fig. 9 presents a performance of different state-of-the-art semi-supervised research works. It is clearly noticed that the research work conducted by Jiang et al. (2014) achieved satisfactory results. They achieved such results as they defined more rules for implicit aspect extraction than previous works and paid more attention to many opinion words' types. Furthermore, both research works of Wang et al. (2013) and Xu et al. (2015) obtained good results.

Fig. 10 presents the performance results of different supervised research works, whereby not all of them used the same data domain, but they share the same supervised method. It is obviously noticed that the research conducted by Mohammed (2016)

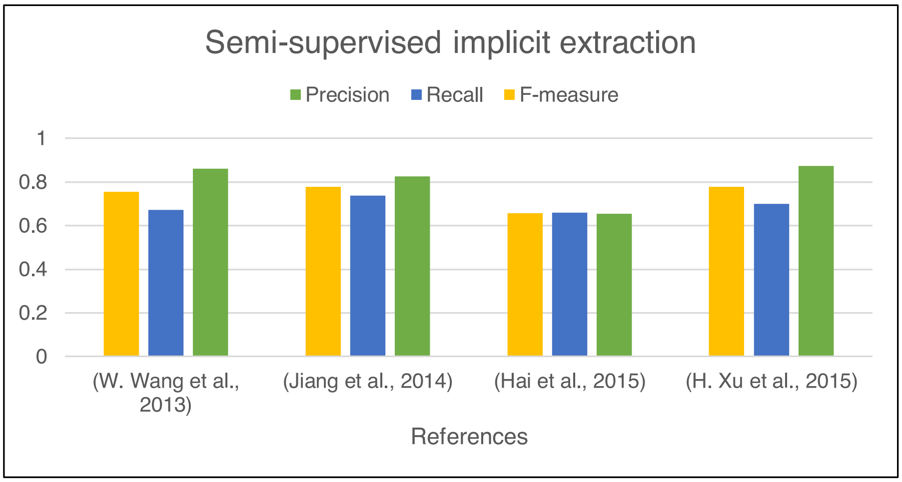

Fig. 9. Performance of semi-supervised research works.

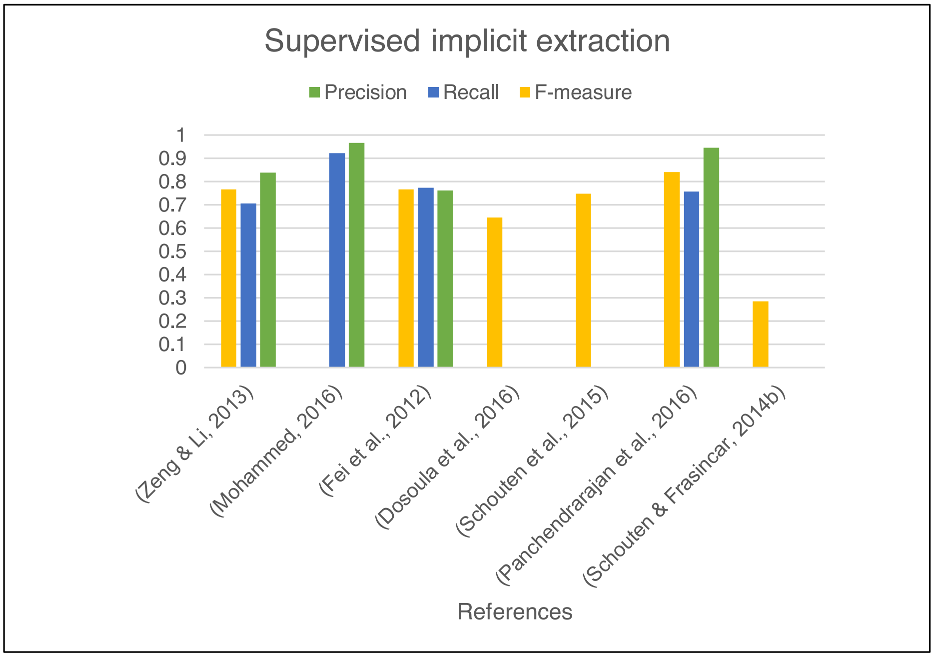

Fig. 10. Performance of supervised research works.

achieved satisfactory results, as they used a hybrid approach which combined both corpus and WordNet with Naïve Bayes classifier. On the other hand, the research work conducted by Schouten and Frasincar (2014b) obtained low *f*-measure. In addition, the technique used by Panchendrarajan et al. (2016) also obtained good performance results due to the use of hierarchy for checking the correctness of implicit aspects and the use of co-occurrence directly between the implicit aspects and opinion words.

Fig. 11 presents a performance of different state-of-the-art research works that extracted implicit aspects and used product reviews. As noticed from Fig. 11, the proposed technique by Mohammed (2016) received very good results. This obtained results not only were based on the used corpus alone, but also the use of another resources of knowledge for implicit aspect extraction. Based on Fig. 11, it is also noticed that many other techniques obtain interesting results. Furthermore, in a research work conducted by Song et al. (2013) it is observed that the result is also satisfactory as they not only based their work on the used corpus, but also exploited the benefits of using other sources of knowledge. Finally, Xu et al. (2015) obtained interesting results as they used two types of relations and pay attention to notional words.

4. Future researches and open problems

Based on the discussion and investigation illustrated in previous sections, which enlightened us with many future research

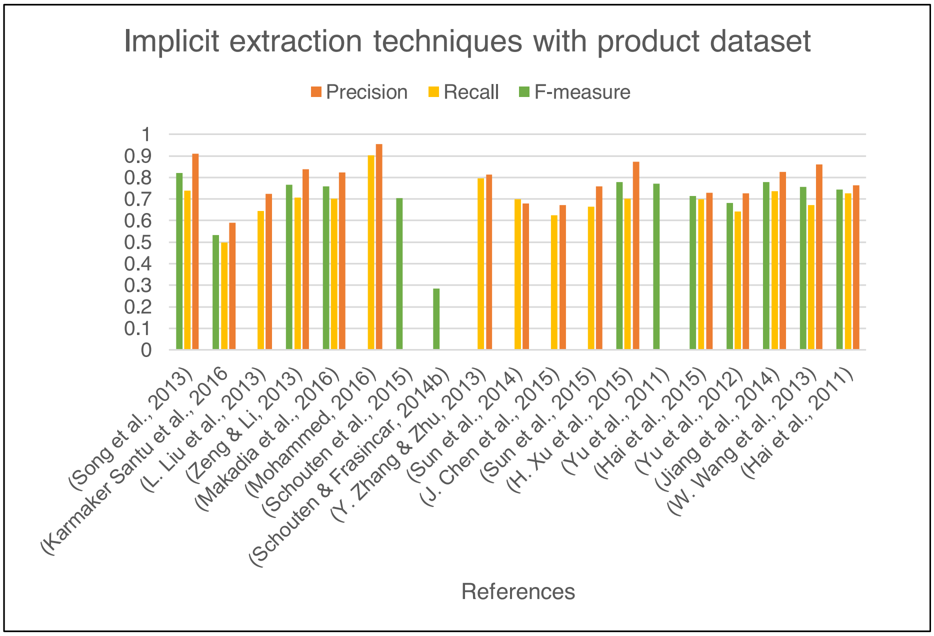

Fig. 11. Performance of implicit aspect extraction techniques that used product reviews in common.

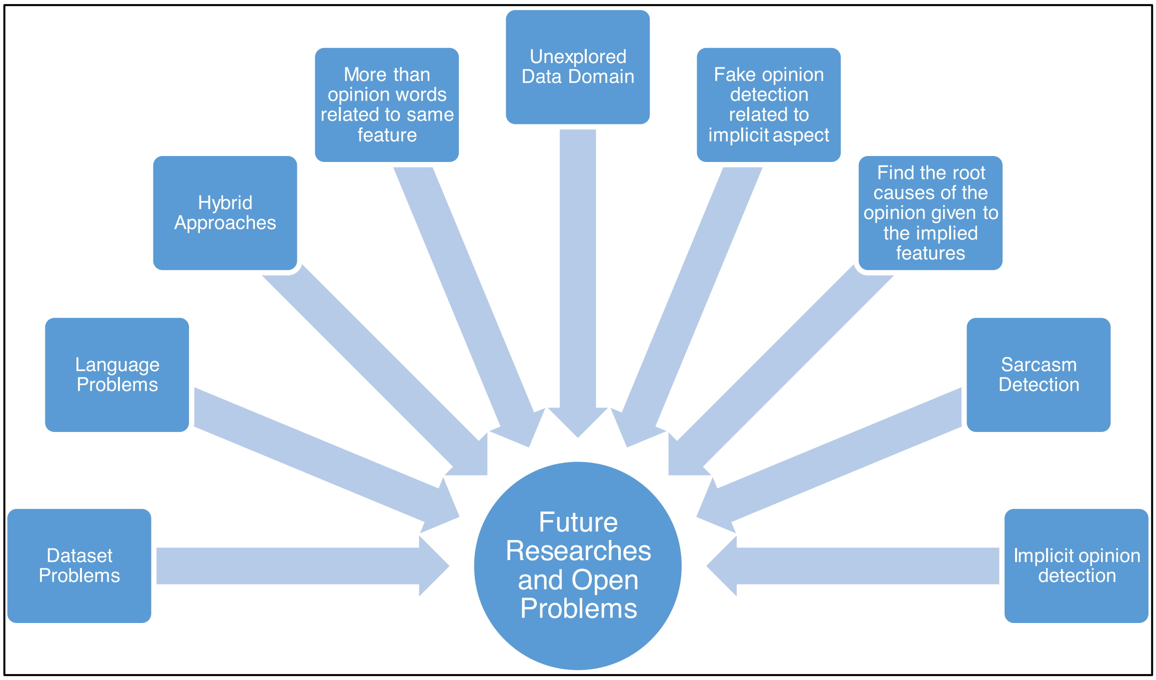

Fig. 12. Future researches and open problems.

directions and uncovered the unsolved problems. Fig. 12 illustrated the main future researches and problems in implicit aspect extraction

As noticed from Fig. 12, there are many areas that still need further investigations and solutions. For instance, there is no standard dataset available for use in implicit aspect extraction testing and evaluation. The lack of public standard datasets opens the doors for creating standard datasets that are publicly available. Another discovered issue from the conducted review is that most of the conducted works are in English and Chinese languages. Other languages are still unemployed in implicit aspect extraction. One possible future direction, is the hybridization of multiple approaches to solve the disadvantages of individual one's by taking the advantages of each included technique.

An unsolved problem is the implicit opinion detection. A technique for finding implicit opinions using not only the implicit feature extraction, but also the implicit opinion related to the target feature is required. Another related issue to find the origin and cause of the opinion directed to the implicit features. The limited data domains that are investigated with most of works concentrated on product reviews. The need of investigating other types of data such as social issues, other type of services, and so on.

Sometimes there is more than one opinion word related to the same features, which indicates that the previous researches have not solved this problem. Another interesting issue needs to take further studies is the detection of fakes and sarcasm opinion related to implicit features.

5. Conclusions

To the best of our knowledge, this is the first work that reviews implicit aspect extraction techniques. There are some significant findings obtained from this review. Studies on implicit aspects extraction were conducted only for some major languages such English, Chinese, and French. However, other languages such as Arabic and Malay are still not being explored, which must be considered for future studies. Our review also shows that the major works in implicit aspect extraction are skewed to unsupervised area, but there is an interesting result for techniques that used supervised methods. Most of the previous works used either unsupervised or supervised approaches, but little works employed the semi-supervised approach. In addition, most of the previous studies focused on implicit aspect extraction on product reviews. Very few studies were seen using hate crime, clothes, tourism reviews and so on. There are many other application areas that are still unexplored such as air flights traveler reviews. Therefore, the focus on product review is not enough and there are other domains that are important and require further future works.

From the previous studies, we also found that many studies conducted in implicit aspect extraction used datasets that were created by the researches themselves and did not publish publicly. The utilization of the private created dataset will result in biased performance results which make the comparison for new researches with the baseline studies more difficult. Moreover, create and publish public dataset make the process more easy and realistic. Future researchers can be done by exploring the gaps which outlined in the review. For example, they can build new standard dataset that can be used in implicit aspect evaluation and experiments to take the advantages and disadvantages of different proposed approaches to make them different and become better solutions. In addition, another possible future research can be exploring the solutions for other languages such as Arabic and Malay, since there is none research on implicit aspect extraction for Arabic and Malay languages. The review also shows that about 64% of the previous studies on implicit aspect extraction used unsupervised methods. Thus, it is another possible future research areas for exploring other methods for implicit aspect extraction.

In conclusion, this review has tackled some important issues that are required by the research community in SA. Detailed literature investigation was conducted with emphasis on implicit aspect extraction, which makes it one of the earliest efforts towards implicit aspect extraction. There are many challenges in SA such as lack of publicly available datasets, hate or sarcasm detection, language difficulties, opinion spam detection, slang preprocessing, and handling of review grammatical errors. These challenges may also affect the implicit aspects extraction. Furthermore, examples of challenges specifically facing by implicit aspects extraction are hidden emotion extraction, the change of implicit sentiment over the time, implicit concept detection, implicit aspect extraction in unexplored languages, implicit opinion detection, and hidden sentiment extraction from figurative expressions. Hence, these findings show that implicit aspect extraction has many aspects can be explored which redeem great opportunities for the researcher to conduct a few studies on it.

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